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Research paper

Face-Based Biometric Recognition System Using LBP, DWT, and SVM Techniques

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Abstract

In biometric security, facial recognition has become a widely adopted contactless alternative to traditional authentication methods such as passwords and fingerprint scanning. This research introduces a novel machine learning-based face recognition system that combines Local Binary Patterns (LBP), Discrete Wavelet Transform (DWT) with Cohen-Daubechies-Feauveau 9/7 filters, and Support Vector Machine (SVM) classifiers. The proposed system operates through three primary stages: image preprocessing, feature extraction, and classification. LBP effectively captures detailed local texture features of the face, while the CDF 9/7 DWT reduces data dimensionality by transforming spatial features into the frequency domain. Finally, SVM is employed to classify the extracted features with high precision. The system is validated using the ORL face dataset comprising 400 images from 40 subjects, achieving a total success rate of 98.22%, outperforming several existing face recognition approaches. Additionally, the model's robustness is evaluated using False Acceptance Rate (FAR) and False Rejection Rate (FRR) metrics across various thresholds, confirming its reliability. Overall, this integrated approach presents a practical, efficient, and accurate solution suitable for real-time biometric face recognition applications.

Keywords: *Face Recognition; Biometric Authentication; Local Binary Pattern (LBP); Support Vector Machine (SVM); Feature Extraction; Machine Learning (ML).*

1. Introduction

With the rapid advancement of digital technologies, safeguarding sensitive data and managing access to digital systems have become essential challenges. Conventional authentication methods—including passwords, physical keys, and RFID cards—are susceptible to risks such as loss, theft, or duplication. As a result, biometric authentication that utilizes individuals' unique physiological and behavioral characteristics has gained recognition as a dependable and secure alternative for verifying identity [1]. Among various biometric modalities, physiological features like fingerprints, iris patterns, and facial characteristics are highly regarded for their distinctiveness and long-term stability. Face recognition, in particular, has gained considerable attention due to its non-intrusive and contactless nature, making it especially relevant in post-pandemic scenarios where hygiene concerns are paramount [2]. Compared to other biometric systems, face recognition offers a low-cost architecture and simpler acquisition processes, which contribute to its increasing adoption across various applications, including security, mobile authentication, and surveillance [3]. However, achieving high recognition accuracy remains challenging due to factors such as varying illumination, facial expressions, occlusions, and background complexities [4]. Traditional methods based on spatial domain features often struggle with these variations, while advanced deep learning techniques, despite their accuracy, require extensive computational resources and large datasets for training [5]. This paper proposes a hybrid machine learning approach that combines Local Binary Pattern (LBP) for capturing detailed local textures, Cohen-Daubechies-Feauveau 9/7 Discrete Wavelet Transform (CDF-9/7 DWT) for frequency domain feature compression, and Support Vector Machine (SVM) for efficient classification. The integrated methodology aims to balance accuracy, computational efficiency, and robustness, providing an effective solution for real-time face recognition. In this paper, a novel algorithm for face-based biometric recognition is presented, which uses LBP, CDF-9/7 DWT, and an SVM classifier, respectively. The use of local face features, frequency domain analysis, and feature compression helps in achieving a higher success rate.

2. Related Works

Face recognition has been an evolving domain in biometric security, with various techniques contributing different levels of accuracy, complexity, and feasibility. This section explores key existing approaches, identifies their limitations, and justifies the need for the proposed hybrid method integrating LBP, DWT, and SVM. Face recognition research has evolved considerably, with approaches spanning classical machine learning to modern deep learning techniques. This section critically reviews selected recent works, highlighting their contributions and shortcomings, which motivate the proposed hybrid method. Prashant Udawant et al. [6] developed a convolutional neural network (CNN) architecture incorporating ResNet layers for face recognition. Using a custom dataset of 3,000 images, their model achieved a high accuracy of 97.5%. While CNNs effectively learn hierarchical spatial features, their success depends on large datasets and significant computational resources, which can limit applicability in resource-constrained or real-time scenarios.

Sakshi Sandeep Phatak et al. [7] presented an AI-enhanced face detection algorithm that integrates Support Vector Machine (SVM) classification with luminance and occlusion detection techniques. This approach improved accuracy in challenging lighting and partial occlusion conditions by focusing on facial feature robustness. However, the method primarily emphasized spatial domain features and did not explore frequency domain representations that could provide complementary information. Ainampudi Kumari Sirivarshitha et al. [8] employed principal component analysis (PCA) using OpenCV libraries for face recognition. Their model yielded an 80% detection accuracy on a custom dataset. Although PCA is computationally efficient and widely used for dimensionality reduction, it may struggle with non-linear variations in facial expressions and illumination, limiting its effectiveness for complex real-world conditions. Md Khaled Hasan et al. [9] provided a comprehensive review of various face detection techniques, categorizing methods into neural networks, feature-based, image-based, and statistical approaches. They highlighted the trade-offs between accuracy, robustness, and computational cost across these methods. Their survey underscored the need for hybrid approaches combining multiple feature extraction and classification techniques to balance performance and efficiency. Gurlove Singh and Amit Kumar Goel [10] explored classical digital image processing-based face recognition using Eigenface and Fisherface methods, achieving around 90% accuracy. These methods are straightforward and interpretable but are sensitive to lighting changes and facial pose variations, which affect robustness.

Dilpreet Singh Brar et al. [11] focused on real-time face detection tailored for mobile devices, using gradient-based CNN and ResNet algorithms. Their system aimed to reduce processing complexity while maintaining accuracy, addressing challenges in deploying deep learning models on limited hardware. However, the trade-off between model size and accuracy remains a concern, especially for low-power devices. Their survey pointed to a gap in hybrid models that balance efficiency and accuracy. The examined literature demonstrates a wide array of facial recognition approaches, including traditional methods such as PCA and Eigenface, as well as sophisticated deep learning models like CNNs and ResNets. Although deep learning methods exhibit enhanced accuracy, they often need considerable computing resources and extensive annotated datasets, rendering them problematic for real-time or resource-constrained settings. In contrast, conventional approaches provide computing efficiency but lack resilience to changes in light, posture, and occlusion. Hybrid methodologies that combine machine learning classifiers, such as SVM, with spatial domain characteristics have shown encouraging outcomes in improving detection accuracy in difficult settings. Many recent studies mostly emphasize spatial characteristics, overlooking frequency domain research that might enhance feature representation and noise resistance. Inspired by these discoveries, the proposed work presents an innovative hybrid approach that integrates local texture extraction using LBP, frequency domain feature compression using CDF-9/7 DWT, and robust classification employing SVM. This integrated technique seeks to use the synergistic capabilities of spatial and frequency domain characteristics, attaining a balance of accuracy, computing efficiency, and real-time application.

3. Proposed Architecture

The flowchart of the proposed face recognition algorithm is shown in Fig. 1, which consists of pre-processing. Feature extraction, classification, and recognition blocks, respectively. The database and test face images are pre-processed to make them suitable for the algorithm. Those processed images are then used to extract the corresponding features using a feature extraction block, which consists of windowing, CLBP, and DWT blocks, respectively. Now the database features and test features are matched using a threshold-based classifier, which helps in accurate face detection.

3.1. Face database

The 400 images of 40 persons from the ORL (Olivetti Research Laboratory) database [12] are considered for testing the proposed algorithm. Different times, luminance, and facial expression are considered for capturing the face image. Moreover, the uses of black and white format with a black background are used here, which makes this database suitable for testing any face recognition algorithms. Ten sample images of ORL databases are shown in Fig. 2.

3.2. Pre-processing

The raw database images are not suitable for algorithmic processing, which gives the requirements of a pre-processing block. It consists of resize and filtering blocks, respectively.

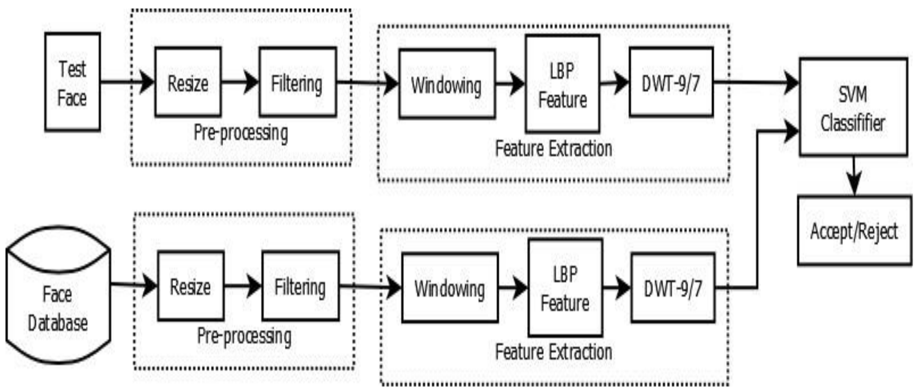

Fig. 1: Proposed Face Recognition Algorithm.

Fig. 2: Ten Sample Face Images of the ORL Database.

3.2.1. Resize

The size of the ORL database images is 92×112, which is not a standard size for any image processing algorithm. So, the size of the database images is converted to standard size (256×256) [13], which is shown in Fig. 3.

(A) Input Image

(B) Resized Image Figure

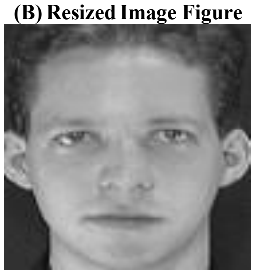

Fig. 3: Image Resize.

3.2.2. Filtering

The high-frequency edges present in the ORL databases are minimized by using a digital filter, which increases the detection accuracy. The two-dimensional Gaussian filter [14] is used in this case, which is given in Equation 1.

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\pi^2}} \tag{1}$$

Here, x represents the horizontal distance from the origin, and y denotes the vertical distance from the origin. The parameter σ corresponds to the standard deviation of the Gaussian distribution. To reduce high-frequency components, this study utilizes a 3×3 Gaussian mask. The specific values of the 3×3 Gaussian mask are presented as follows:

$$\text{Gaussian MAsk} = \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \tag{2}$$

The filtered image is shown in Fig.4

(A) Resized Image

(B) Filtered Image

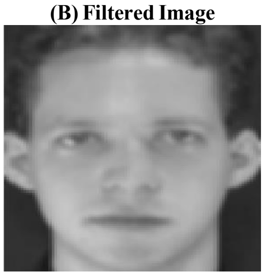

Fig. 4: Filtered Image.

3.3. Feature extraction

The Feature extraction block consists of Windowing, CLBP Features, and DWT blocks, respectively, which are explained briefly in the section below.

3.3.1. Windowing

The pre-processed images are converted into a finite number of pre-defined overlapping matrices, which helps in extracting features effectively using various feature extraction techniques. For this implementation, 3×4 matrices are used, which are shown in Fig.5.

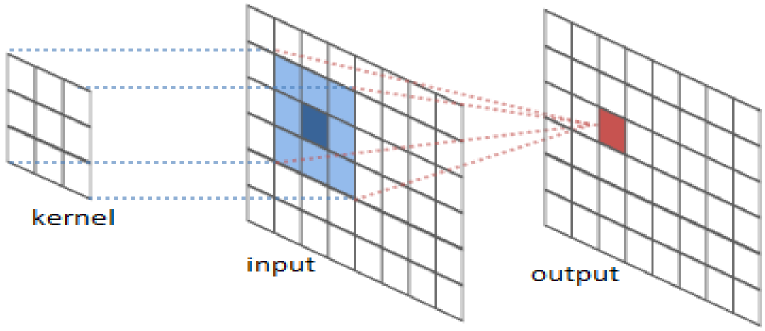

Fig. 5: Sliding Window.

3.3.2. LBP features

The facial feature of any person is normally divided into different parts of the face, which are known as microtexture. The Local Binary Pattern (LBP) is commonly used to extract it [18]. The LBP operator normally considers 3×3 overlapped image sub-matrices and calculates the value of the middle pixel with the help of nearby values, where clockwise values are considered, starting from the top left corner. The middle value is considered a threshold, which is shown in Fig.6.

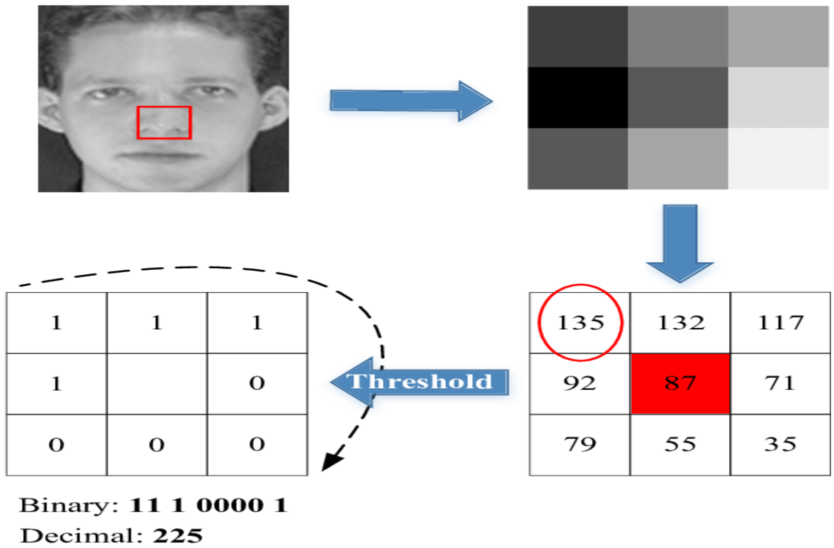

Fig. 6: Local Binary Pattern-Based Feature Calculation.

The LBP equation of a given image sub-matrix whose middle pixel is located at (x,y) can be written as

$$LBP_{(x,y)} = \sum_{n=0}^{N-1} 2^n . s\{I_n(x,y) - I_c(x,y)\} \quad (3)$$

Where, I_c corresponds to the grey value of the center pixel (x, y),
and I_n to the grey values of the 8 surrounding pixels. The threshold function is then written as

$$S_k = \begin{cases} 1 \text{ if } k > 0 \\ 0 \text{ Otherwise} \end{cases} \quad (4)$$

The LBP features of an ORL database face image (first person, first face image) along with the corresponding ing histogram are shown in Fig.7

(A) **(B)**

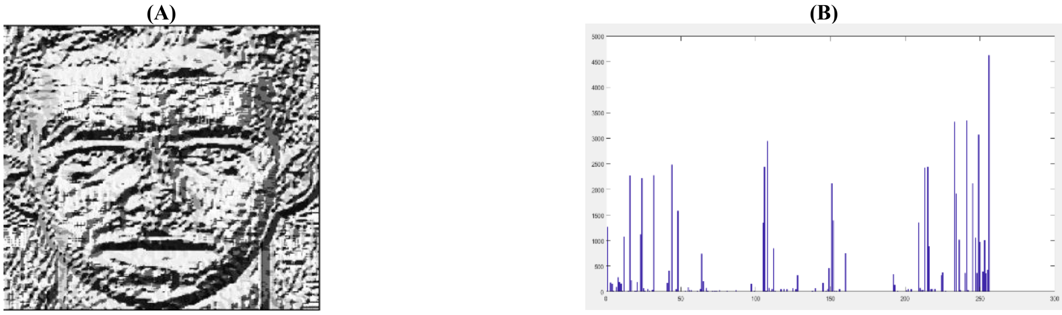

Fig. 7: (A) and (B): Features of Face Image. (A) LBP Feature (B) Corresponding Histogram Fig.7. LBP

3.3.3. Discrete wavelet transform

Wavelet transform is used to convert a time domain signal into the corresponding time-frequency domain, which can be able to extract better features from the input non-stationary signal with tuneable time-frequency adjustment. The discrete wavelet transform (DWT) is used in this paper, which can be mathematically expressed.
[16-17] as

$$X_{a,L} = \sum_{k=1}^{N} X_{a-1,L}(2n-k) \times g(k) \quad (5)$$

$$X_{a,H} = \sum_{k=1}^{N} X_{a-1,L}(2n-k) \times h(k) \quad (6)$$

k=1

In this context, g[n] represents the low-pass filter responsible for extracting the low-frequency components, while h[n] denotes the high-pass filter used to capture the high-frequency components.
The probability density function (PDF) equation is then the block implementation of DWT, as shown in Fig.8.

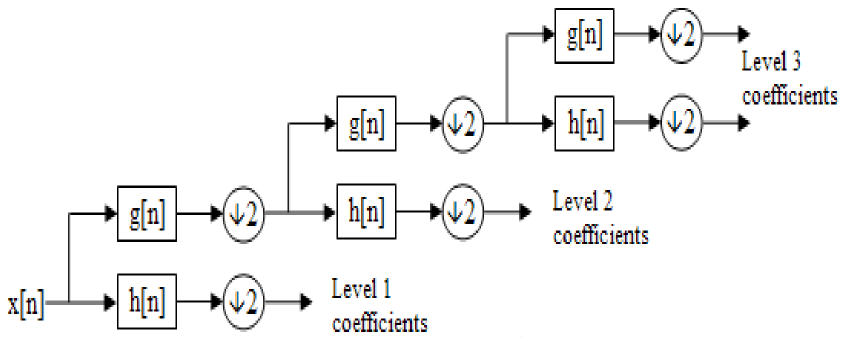

Fig. 8: Forward Discrete Wavelet Transform Architecture.

Once the face data has been decomposed through wavelet transformation, a thresholding process is employed to eliminate signals containing artifacts. The remaining components are then combined to reconstruct a clean and refined signal. To generate time-frequency features, the Cohen-Daubechies-Feauveau (CDF)-9/7 DWT is considered. The filter coefficients are given in Table 2 [19] to implement the CDF-9/7 DWT; the filter coefficients are the Low Pass Filter (LPF) and High Pass filter (HPF).

Table 1: Filter Coefficients of CDF-9/7 DWT [19]

n	Analysis Band		Synthesis Band	
	LPF	HPF	LPF	HPF
0	0.602949018236360	1.115087052457000	1.115087052457000	0.602949018236360
1	0.266864118442875	-0.591271763114250	0.591271763114250	-0.266864118442875
2	-0.078223266528990	-0.05754326228500	-0.05754326228500	-0.078223266528990
3	-0.016864118442875	0.091271763114250	-0.091271763114250	0.016864118442875
4	0.026748757410810	—	—	0.026748757410810

Requires double floating points, which increases the overall complexity and simulation time. To overcome this problem, the filter coefficients are derived from the LeGall CDF-5/3 DWT equation with the help of the Lagrange Half Band Filter (LHBF) equation [20]. The modified equations are then.

$$low_{\frac{9}{7}}(i) = -\frac{1}{8}x(i-2) + \frac{1}{4}x(i-1) + \frac{23}{32}x(i) + \frac{1}{4}x(i+1) - \frac{1}{8}x(i-2) + \frac{1}{64}x(i-4) + \frac{1}{64}x(i+4) \quad (7)$$

$$high_{\frac{9}{7}}(i) = -\frac{1}{8}x(i-2) + \frac{1}{4}x(i) - \frac{1}{8}x(i+2) - \frac{1}{32}x(i-1) - \frac{1}{32}x(i+1) + \frac{1}{32}x(i-3) + \frac{1}{32}x(i+3) \quad (8)$$

The wavelet transformation used in this paper converts time domain features into frequency domain features. As a result, among all four bands, only the LL band is considered in this case, which also performs compression of the dataset.

4. Support Vector Machine

The entire datasets are divided into two classes depending upon a hyperplane as a boundary in the SVM technique, which can be divided into two conditions. For a dimensional vector space, let us consider the hyperplane equation.

$$W^T x + b = 0 \quad (9)$$

Where, w is a normal hyperplane
To find the w and b parameters, the category margin of the equations can be written as

$$W^T x + b = \pm 1 \quad (10)$$

If we assign the target classes as ±1 and attempt to determine the appropriate values of w and b from the dataset, two scenarios arise: (i) when w is perpendicular to the hyperplane and the margins on both sides are equal in distance, and (ii) when w is perpendicular to the hyperplane but the margins differ in distance. These cases are illustrated in Fig.9.

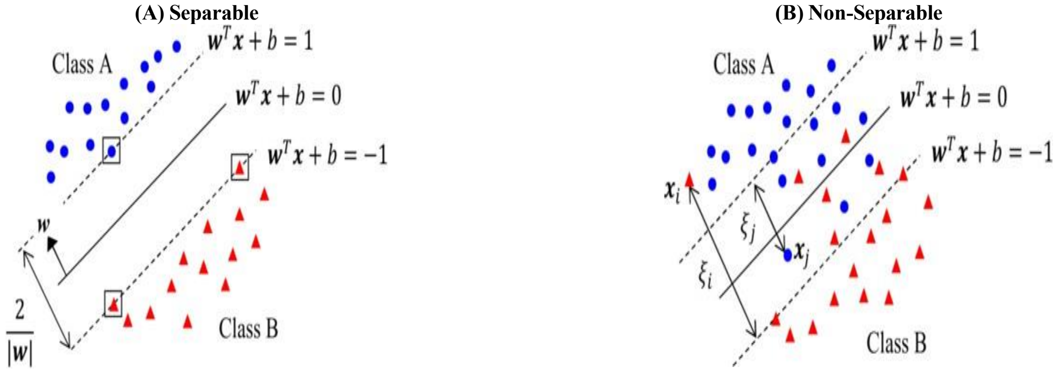

Fig. 9: Operation of Support Vector Machine.

But these kinds of scenarios do not occur when any real-time datasets are considered. Moreover, it is necessary to fit the test dataset into the training dataset for classification. To do this normal decision boundary based on best best-fitting and generalized fitting curves is considered, which is shown in Fig.10.

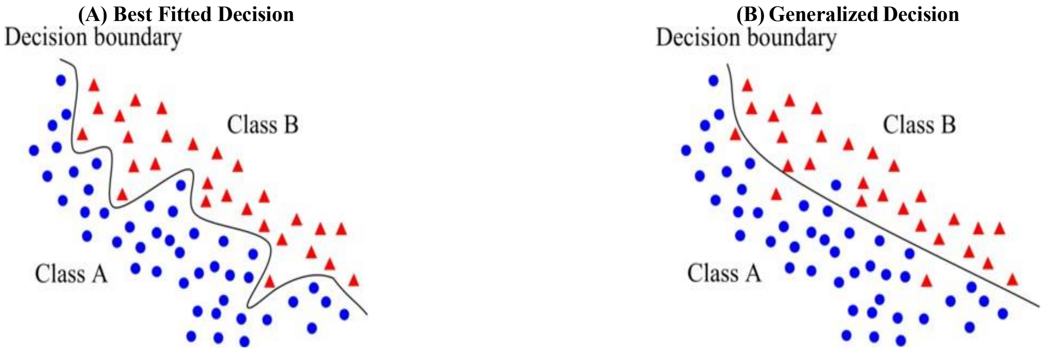

Fig. 10: Nonlinear SVM Classification.

5. Performance Analysis

5.1. Mathematical model

The TSR, FAR, and FRR are used to calculate the performance of the proposed algorithm. The corresponding equations used to calculate the above-mentioned parameters are given in Equations 11 to 13, respectively [15].

$$\text{Total Success Rate (TSR)} = \frac{\text{No.of authorized persons correctly matched}}{\text{Total No.of persons in the database}} \times 100 \tag{11}$$

$$\text{False Rejection Rate (FRR)} = \frac{\text{No.of authorized persons rejected}}{\text{Total No.of persons in the database}} \times 100 \tag{12}$$

$$\text{False Acceptance Rate (FAR)} = \frac{\text{No.of unauthorized persons accepted}}{\text{Total No.of persons in the database}} \times 100 \tag{13}$$

5.2. Simulation result

The proposed machine learning based face recognition algorithm is coded using standard MATLAB-based coding [13] method and implemented on MATLAB 2017A tool. For this implementation, 40 persons of ORL databases are used, and the detection accuracy for different PID: POD are tabulated in Table 2 as

Table 2: Detection Accuracy for Different PID: POD

Sl. No.	PID	POD	%TSR
1	30	10	95.19
2	20	20	98.22

The TSR versus Threshold Graph for the proposed algorithm is given in Fig.11, which shows that the true acceptance rate is 98.22% above threshold 0.3.
Complexity, Computation Theory, and Computation Theory Applications:
A significant difference of the suggested LBP + DWT + SVM method over the use of CNN lies in its low computational effort. Although CNNs usually have millions of parameters, which require ubiquitous high-performance GPUs to train and infer, compared to the processing of being run on the GPUs, the proposed method can run far more efficiently without the need for using specialized accelerated hardware.

This is due to the efficiency of LBP and CDF-9/7 DWT lightweight operations in feature extraction and support vector machine (SVM), in scale linearly with the number of support vectors.

Initial MATLAB runtime testing 2017A with the standard desktop computer processor (Intel i5, 8 GB RAM) shows that the proposed approach takes less than 50 ms to process an image in under 50 ms which is possible to be sufficient to work in real-time applications.

- The lower computing expense suggests several applications, especially in constrained settings:
- Mobile verification: Smartphones or tablets do not require any cloud operations to log in.
- IoT devices: Embedding them on the bottom of traveling boards (e.g., Raspberry Pi) with a home connection and home security.
- Access to low-power systems: It can be employed in remote facilities where it is not possible to have access to high-performance computers.
- Surveillance systems: True live view that does not need server-level processing power.

The high accuracy (98.22 % TSR) and comparatively low hardware requirements precondition successful implementation of the suggested approach in the real world, in cases when the CNN-based solutions might prove inadmissible.

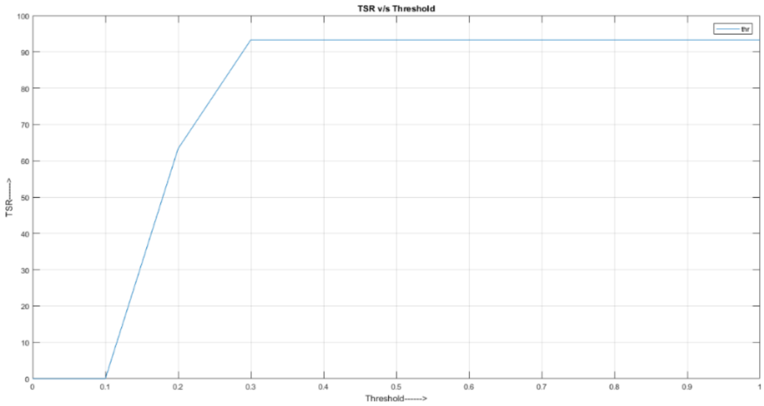

Fig. 11: TSR Verses Threshold Graph.

The FRR versus Threshold Graph for the proposed algorithm is given in Fig.11, which shows that for lesser threshold (less than 0.2) produces a lesser false acceptance rate.

6. Performance Comparisons with Existing Techniques

In this section, the performance parameters of the proposed algorithm are compared with the existing similar performance parameters of the existing techniques. To get the performance comparison with others.

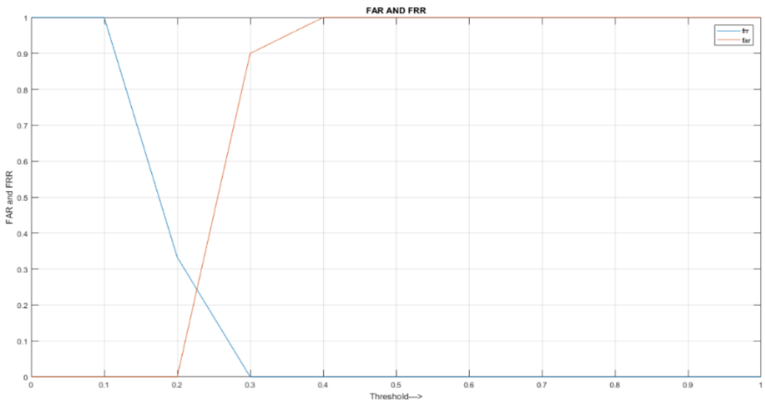

Fig. 12: FRR Versus Threshold Graph.

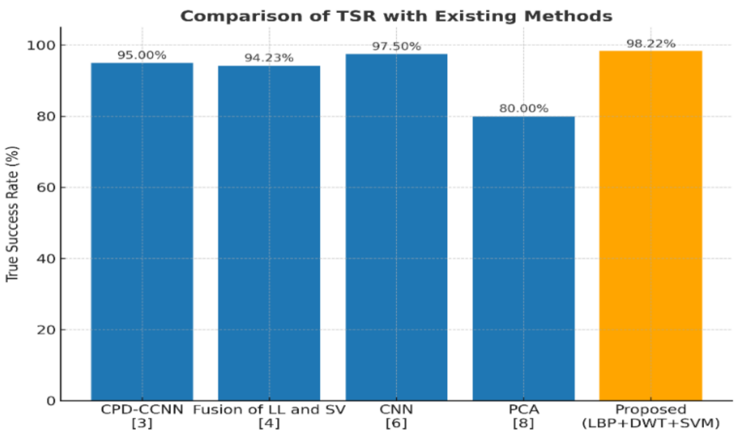

Fig. 13: Comparison of TSR with Existing Methods.

Related techniques, it is necessary to perform the performance parameter comparisons with various similar existing techniques, which is done in Table 3. From the table, it can be seen that the proposed algorithm is better than existing ones in terms of detecting disease accurately. The Fig.13 shows the Comparison of TSR with Existing methods.

Table 3: Comparisons with Existing Techniques

Authors	Techniques	TSR
Kamel Hussein Rahouma and Amal Zarif Mahfouz [3]	CPD-CCNN	95%
Shivalila Hangaragi et al. [4]	Fusion of LL and SV Coefficients	94.23%
Prashant Udawant et al. [6]	CNN	97.50%
Ainampudi Kumari Sirivarshitha et al. [8]	PCA	80%
Proposed	LBP Feature+DWT-9/7+SVM	98.22%

7. Conclusion

The paper proposed a strong and effective face recognition solution that works as a synergistic combination of Local Binary Pattern (LBP), Cohen-Daubechies-Feauveau 9/7 Discrete Wavelet Transform (CDF-9/7 DWT), and Support Vector Machine (SVM). The proposed solution has a high recognition rate of 98.22 percent on the ORL database as a result of pre-processing, local texture extraction, and frequency domain feature compression, which are on par with and superior to several of the latest methods, including CNN and PCA-based systems. In comparison to models based on deep learning, the proposed method would be much cheaper in terms of computation at no trade-off of accuracy. The runtime analysis indicates that it can simply run within real-time range on ordinary computers, and it is therefore quite appropriate for resource-constrained devices like smartphones, embedded systems, and Internet of Things platforms. Such computational effectiveness and high resilience to illumination changes, changes in facial expressions, and even pose make it promising in real-life settings such as mobile-based authentication, low-power surveillance, and access control devices. Although the outcomes are optimistic, the fact that the ORL dataset has been used restricts the outcomes. One of the future works will be to test the performance on bigger and more varied sets of data, like LFW, VGGFace2, and CASIA-WebFace. Other directions are the consideration of Equal Error Rate (EER) in the analysis of performance, DWT integration of lightweight CNN architectures, and adaptation of the system to real-time color and 3D facial recognition. Such enhancements will further be more applicable in sensitizing the suggested system in contemporary biometric security applications.

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